Identifying Community Fire Hazards from Citizen Communication by Applying Transfer Learning and Machine Learning Techniques

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Zhao-Ge Liu[1], Xiang-Yang Li[1], Grunde Jomaas[2]

[1] School of Management, Harbin Institute of Technology, Harbin 150001, China;

[2] School of Engineering, University of Edinburgh, Edinburgh EH9 3FG, UK.

Corresponding author:
Zhao-Ge Liu
Telephone number: +86 18800427198
E-mail: zhoageliu@hit.edu.cn

Abstract:
A cross-region transfer learning method is proposed to identify community (e.g. car parks, public spaces and shopping centers) fire hazards based on text input provided by community members. The key component of the method, which also accounts for data imbalance, is an improved transfer component analysis (TCA) that is embedded with a local discriminant analysis (LDA) to transfer non-local rich knowledge to the fire hazard identification of local communities with an insufficient number of samples. In addition, a fire hazard knowledge map is established and applied to supplement the missing key features for fire hazard identification, and ontology modeling is applied to standardize the text features and reduce the effect of semantic ambiguity brought by cross-region knowledge transfer. The proposed method is verified based on the text data of nine fire hazard classes from Lanzhou and Beidaihe in China. Machine learning experiments show that fire hazard identification performance of all nine classes were improved with the overall accuracy, precision, recall, F1 score and AUC increased by 12%, 15%, 16%, 15% and 15%, respectively. Under data imbalance scenarios, the proposed method outperforms the state of the art methods, such as sampling-based methods, FastText and ULMFiT. The results also show that the proposed method can achieve desired performance with only half of the training samples. These findings illustrate that the proposed method can assist regions by improving fire identification results significantly through knowledge transfer. The proposed approach can be followed to build smart systems for community fire risk management with reasonable performance and high efficiency.

Keyword: Community fire hazards; hazard identification; citizen communication; text classification; machine learning; transfer learning

Declarations:

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(3) *Availability of data and material*: The data in this paper is confidential and can only be shared with permission of the relevant governments.

(4) *Code availability*: The code is open to the public. Anyone who want the code can contact the authors.

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Abstract

A cross-region transfer learning method is proposed to identify community (e.g. car parks, public spaces and shopping centers) fire hazards based on text input provided by community members. The key component of the method, which also accounts for data imbalance, is an improved transfer component analysis (TCA) that is embedded with a local discriminant analysis (LDA) to transfer non-local rich knowledge to the fire hazard identification of local communities with an insufficient number of samples. In addition, a fire hazard knowledge map is established and applied to supplement the missing key features for fire hazard identification, and ontology modeling is applied to standardize the text features and reduce the effect of semantic ambiguity brought by cross-region knowledge transfer. The proposed method is verified based on the text data of nine fire hazard classes from Lanzhou and Beidaihe in China. Machine learning experiments show that fire hazard identification performance of all nine classes were improved with the overall accuracy, precision, recall, F1 score and AUC increased by 12%, 15%, 16%, 15% and 15%, respectively. Under data imbalance scenarios, the proposed method outperforms the state of the art methods, such as sampling-based methods, FastText and ULMFiT. The results also show that the proposed method can achieve desired performance with only half of the training samples. These findings illustrate that the proposed method can assist regions by improving fire identification results significantly through knowledge transfer. The proposed approach can be followed to build smart systems for community fire risk management with reasonable performance and high efficiency.

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1 Introduction

In recent years, the fire statistics in normal buildings have gradually improved [1], but in communities (i.e. public places such as car parks and shopping centers), fire statistics showed the opposite trend. As presented in Table 1, both the frequencies and consequences of community fire incidents have been increasing [2-4] (see table caption for what is regarded as a 'community' in this paper). Examples of significant fires are the car park fires in Liverpool, UK and Stavanger, Norway, as well as the shopping center fire in Kazan, Russia in 2015, which caused 17 deaths and 55 injuries. These incidents and trends suggest the importance of improving fire risk management within communities. As with other fires, community fire incidents are usually caused by a variety of fire hazards, including hazards that increase the likelihood of a fire and that impede escape when a fire occurs (e.g. damaged fire safety facilities, poor environment and the non-availability of escape routes) [5, 6]. To reduce the risks (consequence× probability) associated with community fire incidents, one obvious option is to identify potential fire hazards and remove them before a fire occurs [7].

Table 1 The frequencies and deaths of community fire incidents in recent years. Community fire incidents refer to those that occurred in public places. The baseline places in this table include shopping centers, restaurants, hotels, hospitals and outdoor places such as car parks, rubbish bins and outdoor equipment and facilities.

Year	Annual frequency of community fire incidents			Annual deaths caused by community fire incidents		
	China	England, UK	USA	China	England, UK	USA
2018	150,100	149,927	316,100	325	57	255
2017	146,000	132,477	308,500	319	48	240
2016	143,200	127,416	300,800	313	44	230
2015	141,600	126,684	299,100	275	36	165
2014	140,700	118,525	293,000	271	32	130

Data sources: The official websites of government agencies in relevant countries [2-4].

Traditional fire hazard identification often rely on workers and devices to check whether specific fire hazards exist [8-11]. For example, workers in an industrial plant are informed about the features of common hazards and they can check them regularly when they work. As communities often cover large areas and include complex geometries (e.g. car parks and shopping centers), there is a significant increase in the number of expected fire hazards [12-13]. Typically, it will be both expensive and impractical to apply traditional fire hazard identification methods within communities, because too many resources (including workers and devices) will be needed. In contrast, an inexpensive approach is to identify community fire hazards through the involvement of the 'citizens' of the community space. For example, community workers with no fire hazard duty and community citizens who walk around may observe and report potential fire hazards, thus enabling fast and effective disposal of them. The relevant community organizations will receive the reports and make judgments of what actions to take for the reported fire hazard types according to the hazard descriptions provided.

To facilitate fire hazard identification with citizen communication, a number of community authorities have established service platforms that can help the relevant populations (e.g. citizens and workers) report potential fire hazards whenever and wherever they want [14]. In these service platforms, workers' and citizens' reports are viewed as 'daily service cases', which can be described as the general term for all kinds of cases affecting, or possibly affecting, the daily life of community citizens, such as fire hazards, community facility damage and environmental problems. When fire hazards have been identified, the cases are labeled with corresponding hazard types and transferred to other departments for further processing as shown in Fig. 1.

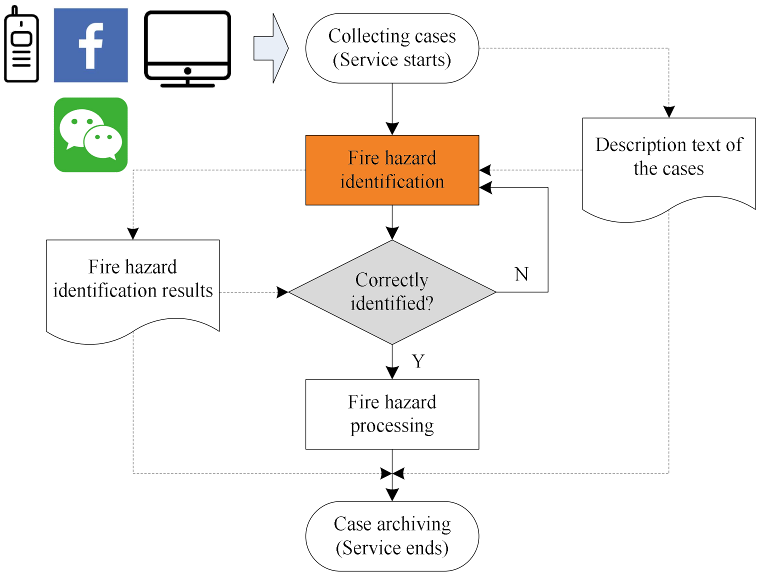

Fig. 1. Community fire hazard identification and processing in community service platforms. In this process, workers' and citizens' reports (which are viewed as 'daily service cases') from various communication channels are analyzed for identifying fire hazards.

However, there is still a lack of effective methods for identifying fire hazards from descriptive input from case texts. Traditional methods tend to rely on human experiences as the number of cases are small and the latent relations (between the descriptive text features and community fire hazards) are relatively simple and clear. For example, several community workers may be appointed to read the service cases and label them according to their knowledge [15]. In recent years, the rapid development of cities has brought about various fire hazards and other community management problems (e.g. environment, facilities and noise), which significantly increases the number of case classes, as well as the complexity of clarifying the latent relations. Faced with so many cases and complex latent relations, relying on manual experience will obviously cause lower efficiency and higher error rates [16]. Moreover, influenced by various language expression ways of community citizens, the noise level of information in the cases is generally pretty high, which further increase the difficulty of dealing with the case information.

In contrast, machine learning (ML) is a good alternative because it relies in full on objective data and can deal with large and noisy datasets. Besides, ML can grasp complex latent relations through statistical analysis and optimization theory, which can improve the accuracy of fire hazard identification. In ML, hazard identification is actually a text classification task. Specifically, complex text features are represented using a vector space and the latent relations (between text features and corresponding hazard types) are obtained using classifiers such as Support Vector Machine (SVM) and Random Forest (RF) [17]. With the support of these ML methods, the identification of fire hazards has the potential to become sufficiently efficient for practical use of the text input from the community population.

However, the direct use of ML algorithms may lead to undesired results of fire hazard identification due to data imbalance. Most existing machine learning algorithms such as SVM and RF work best when the number of samples in each class are about equal. However, there are various daily service cases in community service platforms (apart from fire hazard related cases) and the case data is often severely unequal. In ML fields, this situation is called data imbalance, which may result in classes with small datasets being mistakenly classified as those with big datasets. Fire hazard related classes usually belong to those with small datasets, and are likely to be mistakenly classified. There are totally three data imbalance scenarios of fire hazard identification. The first is the most ideal scenario, where the sample size of all kinds of fire hazard related cases is large enough to achieve desired identification results. The second is the worst scenario, where no fire hazard related case class has enough data to get satisfactory identification results. The third one (which is the one that this study focuses on) is the scenario where partial classes are accompanied with a large sample size (which means high performance can be obtained when testing) using daily service case databases. Such class is called strong class (SC) while other classes are viewed as weak classes (WC). This scenario is more realistic, since the imbalance of data exists in daily service cases.

To solve the data imbalance problem in ML, most scholars prefer sampling-based methods, because these methods are simple and often perform well. For example, under-sampling methods balance the data among different classes by randomly discarding some data of majority class and over-sampling methods do that by repeatedly using some data of minority class [18]. However, sampling-based methods have a hidden assumption that the text features are sufficiently clear so that they can distinguish the minority class from other similar majority classes. This is due to the fact that these methods still use the text features which are extracted from single datasets [18]. When there are not enough samples to provide sufficient text features, the effects of these methods will be limited. For fire hazard identification, this is a significant problem because many case classes have similar feature representation but limited sample sizes. Hence, more effective methods are needed to reduce data imbalance while providing sufficient text features for the classes with small datasets.

As an alternative for dealing with data imbalance, transfer learning (TL) has been increasingly adopted, mainly due to their lenient requirements for sample sizes. The basic principle of TL is to store knowledge gained while classifying cases with big datasets and apply it to the case classification of small datasets [19]. Specifically, TL tries to find a common feature representation between the source domain (cases with big datasets) and the target domain (cases with small datasets) in a latent space, and then building their feature transfer matrices. According to the transferred knowledge, TL methods can be divided into two types. The first method transfers knowledge from Internet and is based on a method that builds a pre-training model from public databases (e.g. Wiki Encyclopedia), and then transfer the parameters of the pre-training model to the target domain. Examples of this model type are the recently released Universal Language Model Fine-tuning (ULMFiT) and Word to Vector model (Word2Vec) [20-22]. The second method tries to find a specific source domain that shares similar feature representation. These methods do not require a pre-training model but require the similarity between domains. This study used these kinds of methods for dealing with data imbalance because the case text of fire hazard identification is usually confidential and thus the transfer of Internet knowledge will be limited. Typical methods such as Large Margin Transductive Transfer Learning (LMTTL) [23] and Semi-Supervised Kernel Matching (SSKM) [24] achieve high performance but require significant computation capacity. TrAdaBoost uses historical samples to help ML with newly added samples, but requires a lot of historical samples [25]. Transfer component analysis (TCA) is another typical method.

It generates the feature transfer matrices by minimizing the distribution difference between the domains in a common feature space. Compared to other methods, TCA is easy to implement and does not require involved calculations or a large number of samples [26, 27]. Hence, TCA was selected for fire hazard identification. As for the source domain for feature transfer, some case classes in other regions have high similarities in content but large sample sizes, which can be used for fire hazard identification under data imbalance.

The biggest challenge when employing transfer learning is that traditional TCA assumes that the contribution of each sample to the domain distribution information is the same [26, 27]. In fact, the contribution varies from sample point to sample point. Generally, the sample points close to the bounding area are more likely to be misclassified. In contrast, the samples far from the bounding area are less likely to be wrongly classified [28]. Herein, an improved TCA method called transfer component analysis with local discriminant analysis (TCA-LDA) is applied to learn the mapping matrices between domains, which helps to incorporate the contribution of each sample point to domain distribution information.

Another challenge is that when using transfer learning, some key text features may need to be supplemented. The identification of some fire hazards requires specific domain knowledge. For example, the identification of some more uncommon fuels like ethanol and crude oil requires the knowledge about the flammability attributes of these fire hazards. However, the key features (such as the flammability attributes and possible fire risks) about fire hazards are often missed in daily service cases as the people who submit the cases are community workers and even citizens. As they are not fire safety specialists, they are less likely to incorporate all needed features in the cases. To overcome the lack of key case features in fire hazard identification, a fire hazard related knowledge map is employed in this paper, which can be viewed as a huge knowledge base storing most key features in fire safety fields and their relations [29]. With the knowledge map, the missing features can be automatically supplemented to the case text through the identification of relevant keywords [30].

At the same time, the semantic ambiguity of the case features in different regions should be considered when transferring knowledge across regions. Compared with formal community reports, the language in community service cases is relatively complex and spoken language is used more frequently for communication [14, 15]. The ambiguity and complexity of the language is quite often augmented by using many words that are synonyms of the feature concept and hence all these words describe the same case feature. Moreover, what adds to the complexity of the language is the use of many hyponyms that all express a sub-concept of a particular feature. For this problem, ontology modeling is most popular used as it can establish the unified association relationship between case features and improve the feature space and TL accuracy [31]. In this paper, ontologies are constructed to establish the standardized forms of case features across regions.

In summary, the aim of the current research is to achieve community fire hazard identification (from daily service cases) for a data imbalance situation. In this process, a transfer learning method (transfer component analysis, TCA) with a local discriminant analysis (LDA) was exploited to improve the identification performance of WC. In particular, mappings of the weak local classes (LC) were learned to the strong non-local classes (NC) in a new latent space in which these classes are highly correlated. As a result, weak case classes can then be directly projected to their corresponding strong classes for Naive Bayes (NB) classification, as illustrated in Fig. 2. To facilitate the effects of this process, a fire hazard knowledge map was built to supplement the key case features and ontology modeling [32] was used to reduce the semantic ambiguity of case features among different regions. The data imbalance scenario where no strong class exists were not illustrated, as this scenario can be included in the scenario where partial classes are strong classes.

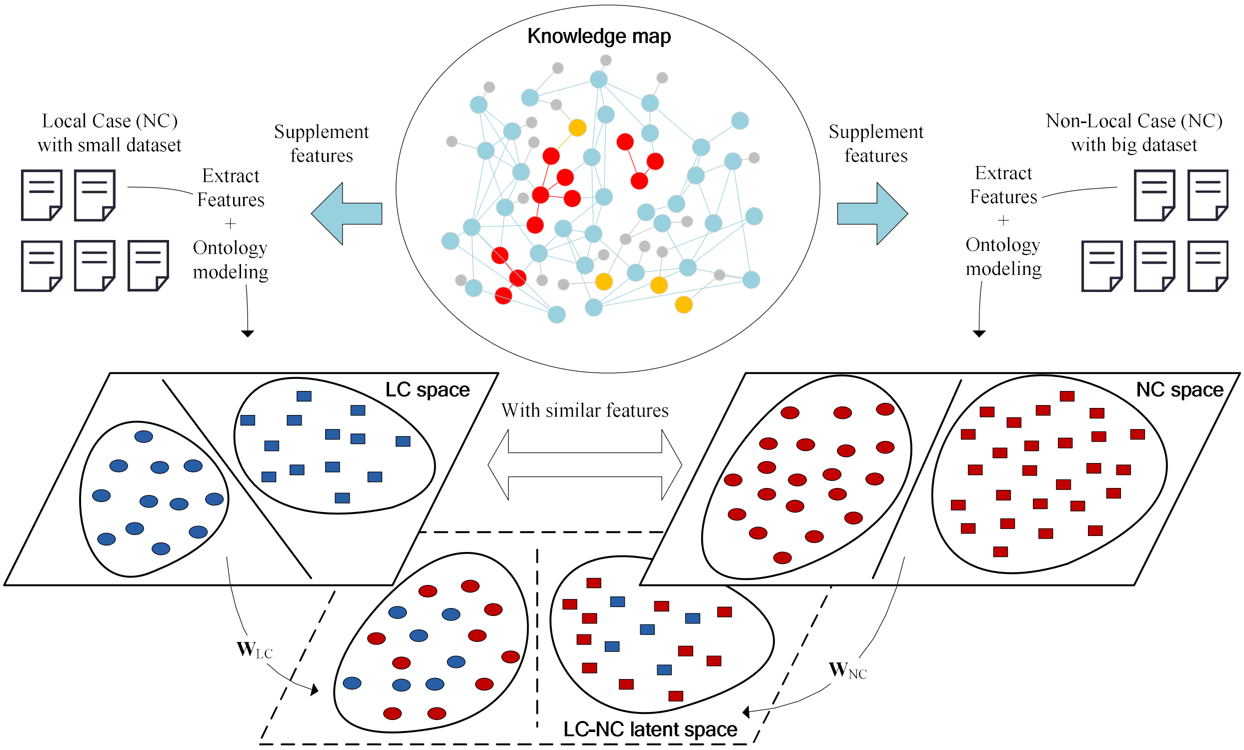

Fig. 2. A basic framework of cross-region transfer learning. The projection matrices $\mathbf{W}_{LC}$ and $\mathbf{W}_{NC}$ are learned using the cross-region mapping algorithms from the local weak class (LC) to non-local strong class (NC) case features. The learned maps are applied to the projected LC features of the test service case samples before an NB classifier is queried for the case class.

2 Methodology

For the abovementioned data imbalance scenario, the proposed method aims to establish the feature mapping between a weak local class (LC) and strong non-local class (NC) and use the mapping to learn the classifiers for LC. The first step of the method is to transform cross-region case text into a numerical representation in the form of a vector. Next, ontology modeling and knowledge maps are used to improve feature representation. Then, transfer learning (TCA-LDA) is employed to establish cross-region feature mapping. Finally, the classifiers are learned with the cross -region case samples. For each case class, half LC cases (with the other half for test) and full size NC cases are used to learn the classifier. The block diagram of the proposed method is summarized in Fig. 3.

The proposed approach outlined in Fig. 3 is an integration of knowledge map, ontology modeling and TCA-LDA. Among them, knowledge maps work for completing case features for feature ontology modeling and feature mapping matrix learning, while ontology modeling provides standardized case features for the cross-domain transfer learning. TCA-LDA is used to learn the feature mapping matrices with the comprehensive and standardized and features provided by fire hazard knowledge map and ontology modeling.

2.1 Datasets and data imbalance situation

2.1.1 Datasets

At the start of 2014, the Chinese government introduced community service platforms nationwide and various pilot communities have gradually built their own community service case databases [33]. With the support of the service platforms, community workers and citizens can report various kinds of threats as soon as they observe them. Sponsored by the National Natural Science Foundation of China (NSFC), the authors conducted surveys in Beidaihe and Lanzhou at the end of 2018. The databases in the two area consist of 19 classes of daily cases with 9 fire hazard related classes and a total 122,274 samples. Among them, there were 101,565 samples in the Lanzhou area and 20,709 samples in the Beidaihe area. These cases were reported by community workers and citizens and had an average text length of 48 words. The distribution of the samples in different case classes is shown in Table 2.

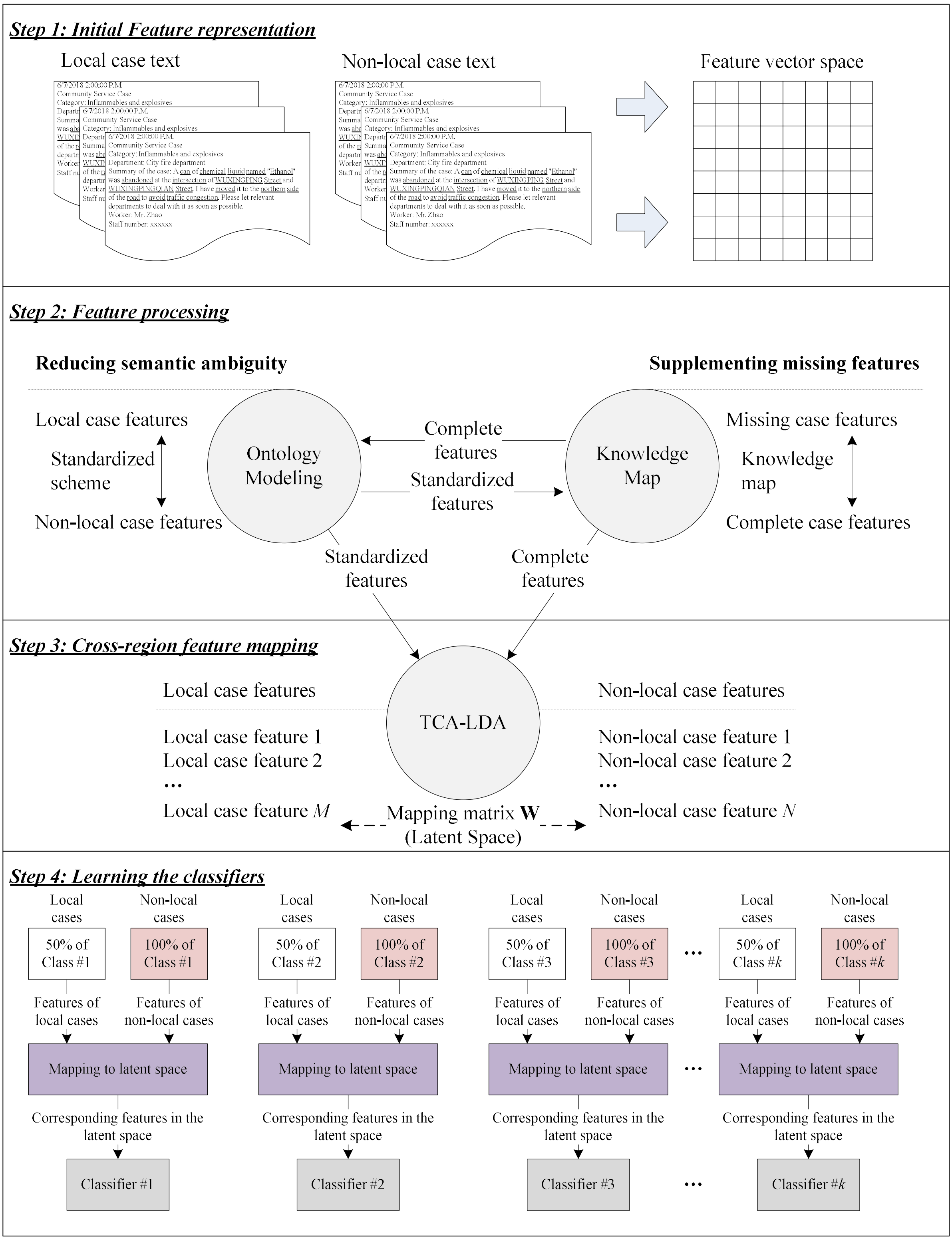

Fig. 3. Block diagram of the proposed method. In this process, cross-region feature mapping is learned with TCA-LDA based on a complete and standardized feature representation scheme provided by ontology modeling and fire hazard knowledge map.

Table 2 The distribution of community daily service cases in the Beidaihe Area and the Lanzhou Area before Dec 2018. Fire hazard related categories are in bold. The data comes from a survey sponsored by National Nature Science Foundation of China (NSFC) in 2018.

General categories of cases	Detailed categories of cases	Number of cases	
		Beidaihe Area	Lanzhou Area
Infrastructures and facilities	Traffic facility damage	624	1249
	Drainage facility damage	1587	8914
	Fire detection facility damage	**82**	**597**
	Fire-fighting equipment damage	**73**	**455**
	Electrical wiring in poor condition	**59**	**574**
City appearance and environment	Exposed garbage	3974	52298
	Illegal posting of ads	3530	27127
	Dirty green areas	3277	770
	Old buildings with poor protection	**267**	**1142**
	Illegal construction of buildings	**540**	**2654**
Street order management	Disorderly parking of bicycles	2876	719
	Disorderly parking of vehicles	1749	533
	Noise	1011	540
	Occupying fire exits	**62**	**375**
	Smoking in restricted area	**79**	**513**
	Inflammables and explosives	**559**	**1096**
Emergencies	**Fire incidents**	**47**	**206**
	Traffic incidents	168	715
	Other incidents	145	1088
Total		20709	101565

The service case databases of the two area were rearranged in detailed categories. By doing so, 19 detailed datasets were generated and each of them contains texts of one case class. To highlight the aim of community fire hazard identification, the current study only shows the classification results of fire hazard related cases. Here, the symbols of each case class and the case distribution of the two area are shown in Table 3. It was observed that the case reports, especially those written by citizens, usually contains spoken language, which may reduce the efficiency of fire hazard identification. Herein, this problem was solved using an ontology modeling method, which will be illustrated in the next section.

Table 3 The symbols of each case class and the distribution of cases in different area. The data comes from a survey sponsored by National Nature Science Foundation of China (NSFC) in 2018.

Symbol	Case class	Number of cases	
		Beidaihe Area	Lanzhou Area
a	Fire detection facility damage	82	597
b	Fire-fighting equipment damage	73	455
c	Electrical wiring in poor condition	59	574
d	Old buildings with poor protection	267	1142
e	Illegal construction of buildings	540	2654
f	Occupying Fire exits	62	375
g	Smoking in restricted area	79	513
h	Inflammables and explosives	559	1096
i	Fire incidents	47	206

2.1.2 Data imbalance situation

The community service platform in Lanzhou was established first (in 2014). Since then, substantial cases have been accumulated. In contrast, the Beidaihe district built a community service platform in 2016, with relatively few accumulated cases, as shown in Table 3. Consequently, there is a significant difference between the data imbalance situations in the two area, which further leads to the difference of performance in fire hazard identification, as shown in Table 4. For the Beidaihe area, the average identification accuracy under current data imbalance situation is only 77%, which is pretty low compared to the 92% in the Lanzhou area. In general, identification performance refers to the classification accuracy of fire hazard related classes, and the aforementioned numbers were calculated using the following expression [34].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where TP is the true positive, TN the true negative, FP is the false positive, and FN the false negative. However, other metrics should also be analyzed when dealing with data imbalance, including the precision, recall, and F1 score, which are calculated as follows [34].

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}, \quad F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{2}$$

In addition, the area under curve (AUC) is also used to evaluate identification performance considering the effects of assumed classification thresholds [18]. The curve refers to receiver operating characteristic (ROC) curve, which is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

Under this data imbalance situation, transfer learning is employed to learn the feature projection matrices from the non-local classes (Lanzhou) to local classes (Beidaihe). Before this process, an important concept should be defined, that is, strong class, which is the service case class that has achieved satisfying identification performance without transfer learning. The satisfying level is set by decision makers. In Fig.4, all the case classes in Lanzhou and partial classes in Beidaihe (such as class #e and #h) can be regarded as strong classes. What this research focuses on is to transfer the weak classes in Beidaihe into strong classes with the support of transfer learning.

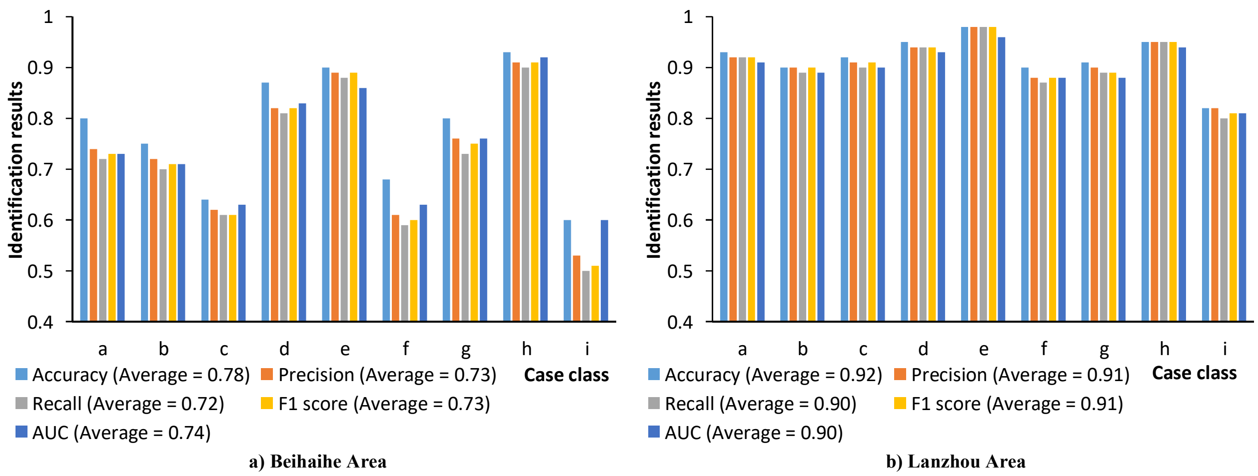

Fig. 4. Fire hazard identification results of a) Beidaihe Area, b) Lanzhou Area across case class under data imbalance. See Table 3 for the case class descriptions.

2.2 Feature representation and processing

To make the feature transfer effective, the careful representation and processing of case text features are needed. In this step, the skip-gram model (a text feature model) was used to represent the features in service case texts, which transfers them into a structured vector space. After that, missing features in daily cases were supplemented with the knowledge map. Finally, the semantic ambiguity of the case features (between the source domain and target domain) was reduced using ontology modeling.

2.2.1 Initial feature representation

In the computer program, case text features are initially represented using a vector space as shown in Fig. 5. Here, the skip-gram model (a text feature model) was employed to realize this in Python [35]. It can be observed from Fig. 5 that the case text is divided into a series of text features (which can be recognized by computer). Based on this, the case text data can be processed and used for transfer learning. It should be noted that the features are extracted from case text using the Jieba tool in Python, which can automatically cut the sentences into words and phrases based on a standard dictionary. Therefore, it is not needed to manually select features from a number of cases. When learning the classification models, each text feature will be assigned a feature weight, and the weights will in turn be adjusted to obtain the best classification performance.

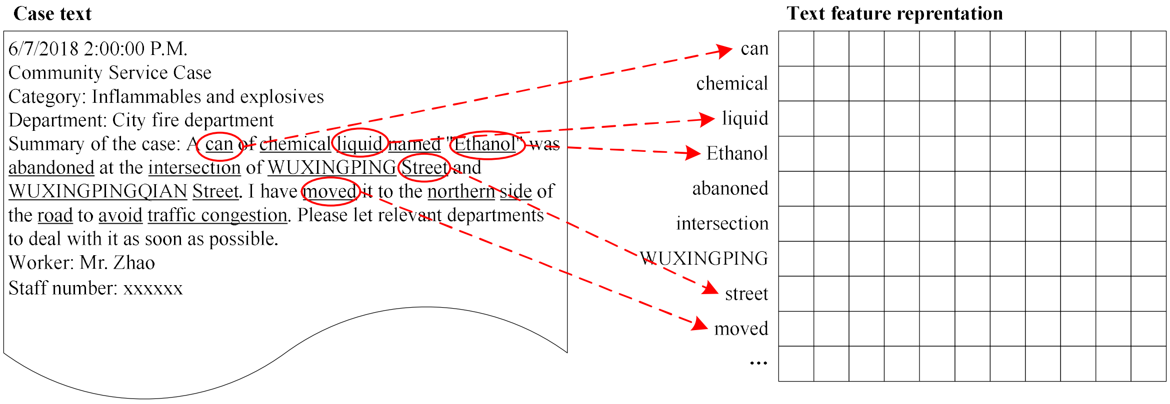

Fig. 5. An example of text feature representation. The case text is transformed into a numerical representation in the form of a vector. For example, the first sentence, 'A can of chemical liquid named…' is represented as the vector '(can, chemical, liquid, …)'.

2.2.2 Supplementing missing features with knowledge map

A knowledge map was established based on Internet open data of the Baidu Encyclopedia, which is similar to the Wiki Encyclopedia but with a greater focus on information provided in Chinese. More than 6000 data items were collected using "fire hazards" and related concepts as key words and the relations of the concepts were extracted with SVM [30]. Using the cluster view in CiteSpace software, the visual knowledge map of fire hazard identification was obtained (Fig. 6).

The knowledge map was then applied to supplement missing features of community service cases. A typical instance is shown in Fig. 7, where the citizen was not aware that the back door also served as a fire exit and therefore only worried about the inconvenience related to it being unavailable for normal pedestrian purposes. Actually, in many Chinese buildings, the back door is used as fire exit and is generally not used for normal person flow. After using the knowledge map, the connections between "back door", "building" and "fire exit" were built and the missing features were supplemented, which makes it easier to identify the detailed hazard category. If the features were not supplemented, the above instance was likely to be labeled as "Disorderly parking of vehicles" as there were no features about fire hazards.

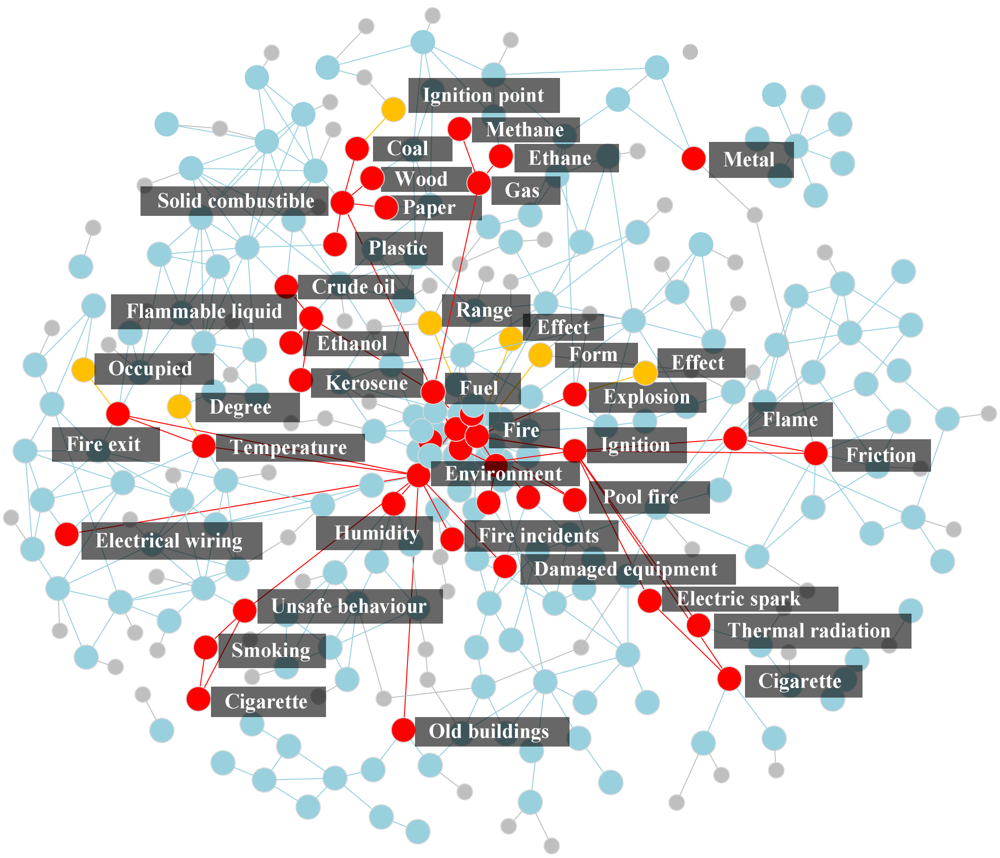

Fig. 6. Knowledge map of the fire hazard identification.
Red nodes and blue nodes represent the hot concepts and general concepts in fire hazard identification, respectively. Yellow nodes indicate the attributes of specific hot concepts and grey nodes denote their attribute values.

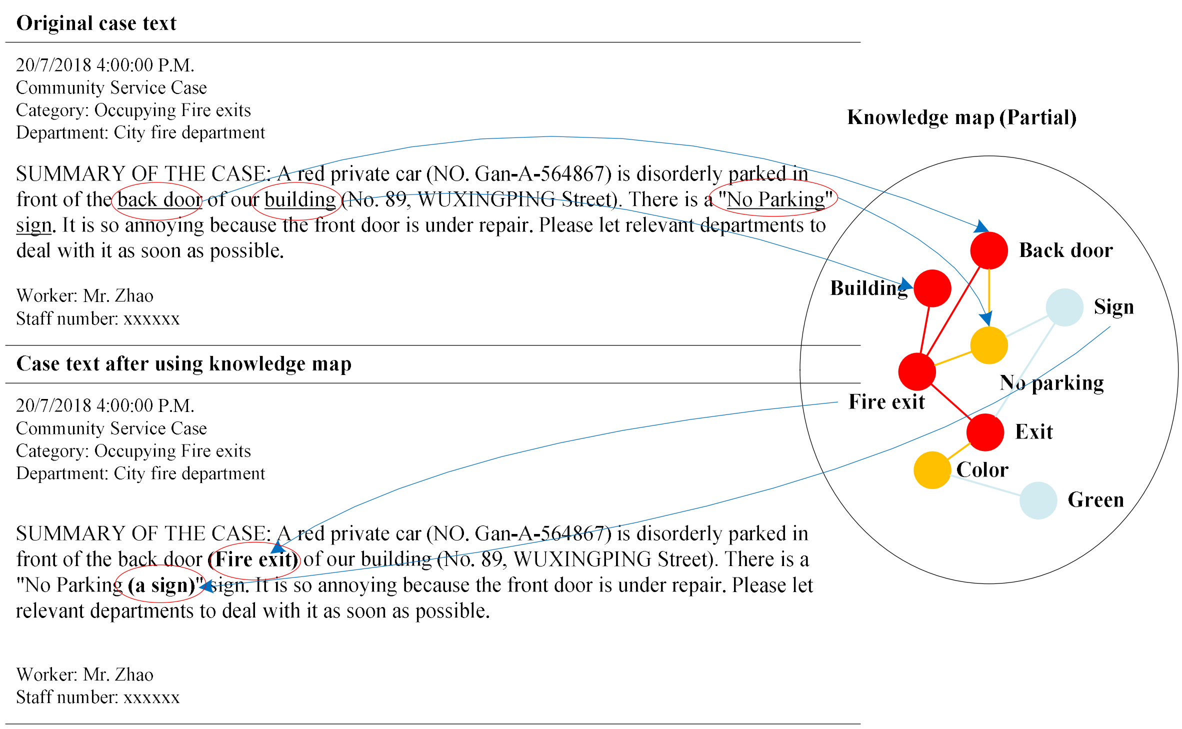

Fig. 7. Application instance of knowledge map in supplementing fire hazard related case features.

2.2.3 Reducing semantic ambiguity with ontology modeling

To reduce the semantic ambiguity of the feature description in different regions, domain ontology fire hazard identification is defined as follows.

Definition 1. A domain ontology is expressed as a two-tuple $O = \langle C, R \rangle$, where C indicates domain concepts, and R indicates relations between the concepts. In detail, $C = \langle C_I, C_N, C_S, C_H \rangle$, where C_I indicates the unique identifier of a concept, C_N indicates the generic term, C_S indicates the synonym set, and C_H indicates the hyponym set. In addition, $R = \langle R_T, R(C_{I1}, C_{I2}) \rangle$, where R_T indicates the types of relations (e.g. 'part of' and 'attribute of'), and C_{I1}, C_{I2} are two concepts that are related semantically.

Take the instance of the case "occupying fire exit". Its domain ontology is shown as follows.

$C_1 = \langle 01, \text{ position, } C_S(\text{location, place, site, locus}), \varnothing \rangle$

$C_2 = \langle 02, \text{ road, } \varnothing, C_H(\text{road, roadside, pavement}) \rangle$

$R = \langle \text{a kind of, } (\text{road, position}) \rangle$

The domain ontologies are used to unify the cross-regional features with same meanings. First, a TF-IDF (term frequency-inverse document frequency) strategy [36] was used to calculate the weights of concepts in the case text and extract concepts with higher weights. Secondly, the dialectal words in these concepts were replaced with the unified words based on the constructed domain ontologies. Finally, the relations of concepts in the ontologies were used to continue searching for concepts and continuously reduce the semantic ambiguity.

The domain ontologies should be updated frequently. With the accumulation of daily service cases, the weights of concepts also change. New concepts are required to be added and low-weight concepts should be removed, so that the domain ontologies can effectively serve to reduce semantic ambiguity and improve knowledge transfer.

2.3 Generating the cross-region feature mapping matrices based on TCA-LDA

The principle of transfer component analysis [19, 27] is to build a common feature representation space (which is called the latent space) where the source domain and target domain have the most similar distribution to transfer the knowledge learned in source domain to the target domain and to obtain the mapping matrix $\mathbf{W}$. Both the source domain A and target domain B have c classes. There are p samples in A, which is expressed as $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_p]$, and q samples in B, which is expressed as $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_q]$.

2.3.1 Local discriminant analysis

In order to distinguish the influences of different sample points on domain distribution, local discriminant weights were assigned for each domain sample and improve text classification effects by restricting the feature mapping of the sample points with small local discriminant weights. The instances of local discriminant analysis are shown in Fig. 8.

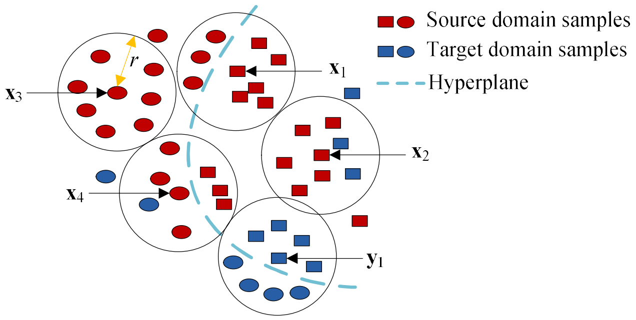

Fig. 8. Instances in local discriminant analysis. The hyperplane represents the boundary of different classes. r represents the radius of the nearest neighbor circles and the value of r is most appreciate if most of the circles cover 3 to 5 samples.

In Fig. 8, there are four sample points $\mathbf{x}_1$, $\mathbf{x}_2$, $\mathbf{x}_3$, $\mathbf{x}_4$ from source domain and one sample point $\mathbf{y}_1$ from target domain. The nearest neighbor circles are drawn with radius r for each of the samples. With the nearest neighbor circles, the calculation method of local discriminant weights is designed with consideration of the sample distribution within the circles. For example, the nearest neighbor circles of $\mathbf{x}_1$, $\mathbf{x}_4$ and $\mathbf{y}_1$ cover samples from different classes, which are of vital importance to the determination of classification hyperplane. As a result, the local discriminant weights of these sample points should be bigger. Another instance is that the nearest neighbor circles of $\mathbf{x}_2$ and $\mathbf{x}_3$ cover the samples all from the same classes, which are less important in determining classification boundary, so the weights should be smaller. From the analysis above, the local discriminant weights are calculated as follows.

$$\omega_i = \frac{\exp\left(-\frac{1}{n_{sd}}\right) + \xi \exp\left(-\frac{1}{n_{td}+\varepsilon}\right)}{\exp\left(-\frac{1}{n_{ss}+\varepsilon}\right) + \xi \exp\left(-\frac{1}{n_{ts}+\varepsilon}\right)} \tag{3}$$

where n_{sd} indicates the number of samples from source domain and with different labels within the nearest neighbor circle of $\mathbf{x}_i$ or $\mathbf{y}_i$, n_{td} indicates the number of samples from target domain and with different labels within the nearest neighbor circle, n_{ss} indicates the number of samples from source domain and with the same label, n_{ts} indicates the number of samples from target domain and with the same label, ξ denotes the value coefficient of the sample points from target domain and is generally above 1 as they are more valuable in determining distribution information. The parameter ε is set in order to avoid zero denominator.

For each sample point $\mathbf{x}_i$ or $\mathbf{y}_i$, sorting the value of ω_i in ascending order. The feature mapping of last s points will be restricted, and that of other sample points will be promoted, which realizes the local discriminant analysis across domains.

2.3.2 Cross-domain transfer mapping

Based on the local discriminant analysis, the traditional TCA process is applied. Set $\mathcal{X} = \mathbf{X} \cup \mathbf{Y}$ as the combined feature space of source domain $\mathbf{X}$ and target domain $\mathbf{Y}$, and $\phi: \mathcal{X} \to \mathcal{H}$ as the feature mapping function from the combined space to the latent space which is needed to be solved. The target of cross-domain learning is to minimize the distance between the $\mathbf{X}$ and $\mathbf{Y}$ in a latent space $\mathcal{H}$. The distance function is as follows.

$$Dist(\mathbf{X},\mathbf{Y}) = \left\| \frac{1}{p}\sum_{i=1}^{p}\phi(\mathbf{x}_i) - \frac{1}{q}\sum_{i=1}^{q}\phi(\mathbf{y}_i) \right\|_{\mathcal{H}}^2 \tag{4}$$

In the equation above, it is difficult to define the explicit expression of the non-linear function ϕ . Consequently, Pan et al. [26] proposed to transfer the problem by converting it into a kernel learning problem and introduced a kernel matrix. The distance function is then converted as follows.

$$Dist(\mathbf{X},\mathbf{Y}) = \mathrm{tr}(\mathbf{KL}) \tag{5}$$

where

$$\mathbf{K} = \begin{bmatrix} \mathbf{K}_{S,S} & \mathbf{K}_{S,T} \\ \mathbf{K}_{T,S} & \mathbf{K}_{T,T} \end{bmatrix} \tag{6}$$

is a $(p+q)\times(p+q)$ kernel matrix, $\mathbf{K}_{S,S}$, $\mathbf{K}_{T,T}$, and $\mathbf{K}_{S,T}$ represent the kernel matrices of source space, target space and combined space, respectively. $L = [L_{ij}] \geq 0$ with $L_{i,j} = 1/p^2$ if $\mathbf{z}_i$, $\mathbf{z}_j \in \mathbf{X}$; $L_{i,j} = 1/q^2$ if $\mathbf{z}_i$, $\mathbf{z}_j \in \mathbf{Y}$; otherwise, $-1/(pq)$. $\mathbf{z}_i$ and $\mathbf{z}_j$ are the elements in the kernel matrix of combined space.

Further, the kernel matrix $\mathbf{K}$ is decomposed as $\mathbf{K} = (\mathbf{K}\mathbf{K}^{-1/2})(\mathbf{K}^{-1/2}\mathbf{K})$, and the corresponding feature vectors can be transformed to a m-dimension space with a $(p+q)\times m$ matrix $\tilde{\mathbf{W}}$. In general, $m \ll (p+q)$ ("$\ll$" means far less than). The matrix $\mathbf{K}$ is then converted into the expression as follows [27].

$$\tilde{\mathbf{K}} = (\mathbf{K}\mathbf{K}^{-1/2}\tilde{\mathbf{W}})(\tilde{\mathbf{W}}^{\mathrm{T}}\mathbf{K}^{-1/2}\mathbf{K}) = \mathbf{K}\mathbf{W}\mathbf{W}^{\mathrm{T}}\mathbf{K} \tag{7}$$

where $\mathbf{W} = \mathbf{K}^{-1/2}\tilde{\mathbf{W}} \in \mathbb{R}^{(p+q)\times m}$ ($\mathbb{R}^{(p+q)\times m}$ is a real matrix with p + q rows and m columns). The distance function defined in Eq. (4) can be then transformed to the expression as follows.

$$Dist(\mathbf{X},\mathbf{Y}) = \mathrm{tr}(\mathbf{K}\mathbf{W}\mathbf{W}^{\mathrm{T}}\mathbf{K}\mathbf{L}) = \mathrm{tr}(\mathbf{W}^{\mathrm{T}}\mathbf{K}\mathbf{L}\mathbf{K}\mathbf{W}) \tag{8}$$

Finally, a regularization term $\mathrm{tr}(\mathbf{W}^{\mathrm{T}}\mathbf{W})$ is used to control the complexity of $\mathbf{W}$, and the kernel learning problem can be expressed as follows.

$$\begin{aligned} \min_{\mathbf{W}} \quad & \mathrm{tr}(\mathbf{W}^{\mathrm{T}}\mathbf{W}) + \mu \times \mathrm{tr}(\mathbf{W}^{\mathrm{T}}\mathbf{KLKW}) \\ \text{s.t.} \quad & \mathbf{W}^{\mathrm{T}}\mathbf{KHKW} = \mathbf{I} \end{aligned} \tag{9}$$

where μ is a trade-off parameter, $\mathbf{I} \in \mathbb{R}^{m \times m}$ is an identity matrix, $\mathbf{H} = \mathbf{I}_{p+q} - 1/(p+q)\mathbf{1}\mathbf{1}^{\mathrm{T}}$ is a centering matrix where $\mathbf{1}$ is a column vector with all ones and $\mathbf{I}_{p+q}$ is also an identity matrix.

2.4 Learning the classifier

Given the feature representation of strong local class (LC) and weak non-local class (NC), the feature matrix $\mathbf{W}$ is learned using improved transfer learning analysis (TCA-LDA). The fire hazard identification of NC is realized with matrix $\mathbf{W}$ using regularized least square regression. In this process, the classifiers are obtained by executing Python's own file, and the optimal values of the regularization parameters are estimated empirically in a grid search manner [37].

3 Experimental results

3.1 Performance of the proposed method

The ML experiments on the proposed approach have been repeated 10 times and then the means of the resulting accuracy, precision, recall, F1 score and AUC have been presented in Fig. 8. The results are also compared to those without knowledge transfer and those without knowledge map, as shown in Fig. 9. Due to the limited space, Fig. 9 only present the identification accuracy, but the results using other metrics showed similar trends, which have been displayed in Table 4.

It is evident that after applying the cross-region transfer learning, the fire hazard identification in all case classes have been improved, with the number of weak classes reduced from 7 to 1 (here, the desired identification accuracy level is set to 85%) and the overall identification accuracy improved by 13%. Especially for class #c, transfer learning improved the accuracy by more than 20%. On the other hand, the effect of feature supplementing on identification improvement is also worth noting. It can be seen from the results that when using knowledge map, the function of transfer learning was further reinforced, with the identification accuracy improved from 87% to 89%. In addition, the effects of data imbalance have been significantly reduced, with precision, recall, F1 score and AUC improved from 73%, 72%, 73% and 74% to 88%, 88%, 88% and 89%, respectively.

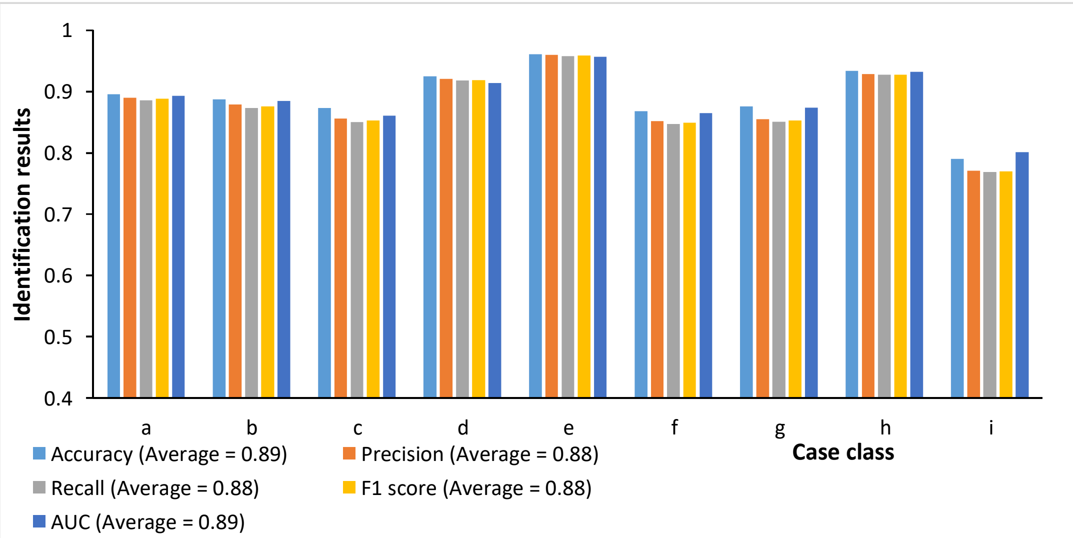

Fig. 8. Identification results when using the knowledge transfer from the Lanzhou Area to the Beidaihe Area. See Table 3 for the case class descriptions. With the knowledge transfer, the identification performance in terms of the five metrics was improved to a similar high level. To avoid similar presentation, metrics were selected to show the results in the next figures.

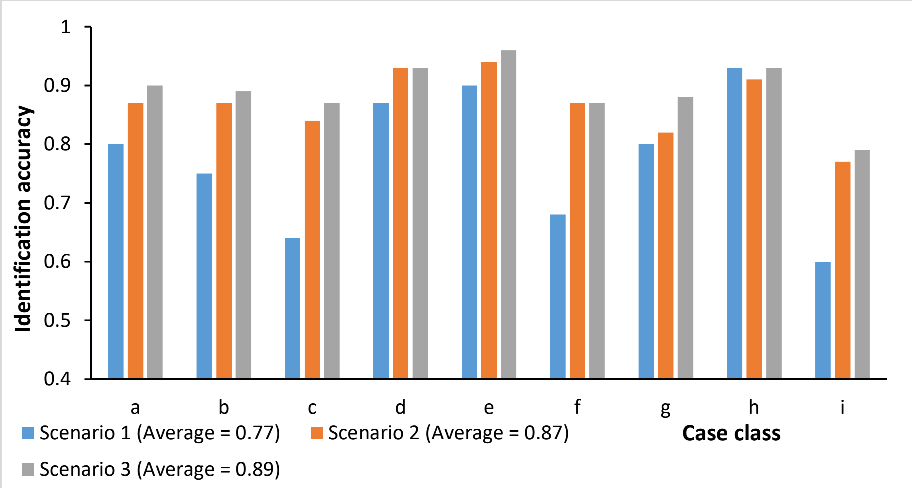

Fig. 9. The identification accuracy under different scenarios. The identification results in other metrics show similar trends (see Table 4). Scenario 1 is the original data imbalance scenario. In Scenario 2, knowledge transfer method is used. In Scenario 3, knowledge map is employed combined with knowledge transfer.

Table 4 Detailed results of fire hazard identification under different scenarios. See Table 3 for the case class descriptions. Scenario 1 is the data imbalance scenario. In Scenario 2, knowledge transfer method is used. In Scenario 3, knowledge map is employed combined with knowledge transfer. Among the metrics, 'A' represents accuracy, 'P' represents precision and 'R' represents recall.

Scenario	Metric	a	b	c	d	e	f	g	h	i	Average
Scenario 1	A	0.80	0.75	0.64	0.87	0.90	0.68	0.80	0.93	0.60	0.77
	P	0.74	0.72	0.62	0.82	0.89	0.61	0.76	0.91	0.53	0.73
	R	0.72	0.70	0.61	0.81	0.88	0.59	0.73	0.90	0.50	0.72
	F1	0.73	0.71	0.61	0.82	0.89	0.60	0.75	0.91	0.51	0.73
	AUC	0.73	0.71	0.63	0.83	0.86	0.63	0.76	0.92	0.60	0.74
Scenario 2	A	0.87	0.87	0.84	0.93	0.94	0.87	0.82	0.91	0.77	0.87
	P	0.85	0.86	0.81	0.92	0.93	0.86	0.80	0.91	0.73	0.85
	R	0.85	0.85	0.81	0.91	0.93	0.84	0.80	0.91	0.72	0.85
	F1	0.85	0.85	0.81	0.92	0.93	0.85	0.80	0.91	0.73	0.85
	AUC	0.87	0.84	0.85	0.92	0.93	0.86	0.81	0.91	0.76	0.86
Scenario 3	A	0.90	0.89	0.87	0.93	0.96	0.87	0.88	0.93	0.79	0.89
	P	0.89	0.88	0.86	0.92	0.96	0.85	0.86	0.93	0.77	0.88
	R	0.89	0.87	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	F1	0.89	0.88	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	AUC	0.89	0.89	0.86	0.91	0.96	0.87	0.87	0.93	0.80	0.89

In general, our results represent a good trade-off between two kinds of data imbalance scenarios: The scenario in Lanzhou area is optimal as all of the case classes are strong classes. However, this scenario needs longer time for case accumulation or powerful policy orientation, which is unrealistic for the communities like Beidaihe, which are still in the early stage of information construction. On the other hand, the worst scenario (where no fire hazard related case class has enough data to get satisfied identification results) can be easily converted to the scenario where partial classes are strong classes due to the huge space for improving identification with non-local cases.

3.1.1 Effect of training sample size

To study the effect of the number of samples on the performance of the mapping approach, the ML experiments were run with increasing number of samples in the learning process gradually in four steps: (1/4, 1/2, 3/4, 1)×Size of the training set from source domain (NC). Table 5 shows the results of these experiments.

It can be seen that using relative sample size proportions of 1/4, 1/2, 3/4 and 1 for learning the mapping, the identification accuracy was improved to 80%, 84%, 87% and 89%, respectively. At the same time, the performance in terms of other metrics (i.e. precision, recall, F1 score and AUC) has also been greatly improved. This is a significant improvement over the identification performance without knowledge transfer (as shown in Table 5). As the number of source domain samples increases, the mapping process will be more efficient and consequently the overall identification performance across all classes are expected to increase.

Table 5 Effect of the sample size on identification results with training sample size of 1/4, 1/2, 3/4, and 1. See Table 3 for the case class descriptions. Among the metrics, 'A' represents accuracy, 'P' represents precision and 'R' represents recall.

Scenario	Metric	a	b	c	d	e	f	g	h	i	Average
1/4 source sample size	A	0.82	0.78	0.69	0.88	0.94	0.71	0.81	0.93	0.63	0.80
	P	0.79	0.76	0.65	0.87	0.93	0.68	0.78	0.92	0.62	0.78
	R	0.79	0.76	0.65	0.86	0.93	0.68	0.78	0.92	0.61	0.78
	F1	0.79	0.76	0.65	0.86	0.93	0.68	0.78	0.92	0.61	0.78
	AUC	0.81	0.76	0.68	0.86	0.93	0.69	0.79	0.93	0.64	0.79
1/2 source sample size	A	0.86	0.83	0.78	0.90	0.95	0.79	0.84	0.93	0.73	0.84
	P	0.84	0.82	0.76	0.90	0.95	0.77	0.82	0.92	0.71	0.83
	R	0.84	0.82	0.76	0.90	0.94	0.77	0.82	0.92	0.70	0.83
	F1	0.84	0.82	0.76	0.90	0.94	0.77	0.82	0.92	0.70	0.83
	AUC	0.85	0.82	0.77	0.90	0.95	0.77	0.83	0.92	0.71	0.84
3/4 source sample size	A	0.88	0.86	0.86	0.91	0.95	0.83	0.85	0.93	0.78	0.87
	P	0.87	0.85	0.85	0.91	0.95	0.82	0.85	0.93	0.75	0.86
	R	0.87	0.85	0.85	0.91	0.95	0.82	0.84	0.92	0.75	0.86
	F1	0.87	0.85	0.85	0.91	0.95	0.82	0.84	0.92	0.75	0.86
	AUC	0.87	0.85	0.86	0.91	0.95	0.82	0.85	0.92	0.76	0.87
Full sample size	A	0.90	0.89	0.87	0.93	0.96	0.87	0.88	0.93	0.79	0.89
	P	0.89	0.88	0.86	0.92	0.96	0.85	0.86	0.93	0.77	0.88
	R	0.89	0.87	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	F1	0.89	0.88	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	AUC	0.89	0.89	0.86	0.91	0.96	0.87	0.87	0.93	0.80	0.89

3.1.2 Effect of semantic ambiguity

The effect of the semantic ambiguity between regions was also investigated. In this regard, two experiments were conducted. In the first experiment, ontology modeling was used to reduce the semantic ambiguity, as illustrated in section 2.2.3. In the second experiment, knowledge transfer was carried out directly without ontology modeling. The experiments were run 10 times with shuffling the samples before dividing them into training and testing sets, and the means and standard deviations were reported. The identification results are shown in Fig. 10. Due to the limited space, Fig. 10 only present the identification accuracy, but the results using other metrics showed similar trends, which have been displayed in Table 6.

As shown in Fig. 10, when not using ontology modeling to standardize the cross-region features, the effect of transfer learning on fire hazard identification is limited, with only a small improvement of the overall identification accuracy (5%) and the identification accuracy of some classes was even not improved (e.g., #e). In contrast, the identification accuracy was greatly improved by 12% when using the ontology models to support feature relation mining. The results in terms of other metrics (i.e. precision, recall, F1 score and AUC) present similar findings. The above results illustrated the negative influence of semantic ambiguity on identification results when applying cross-region knowledge transfer, and the effect of ontology modeling in reducing semantic ambiguity.

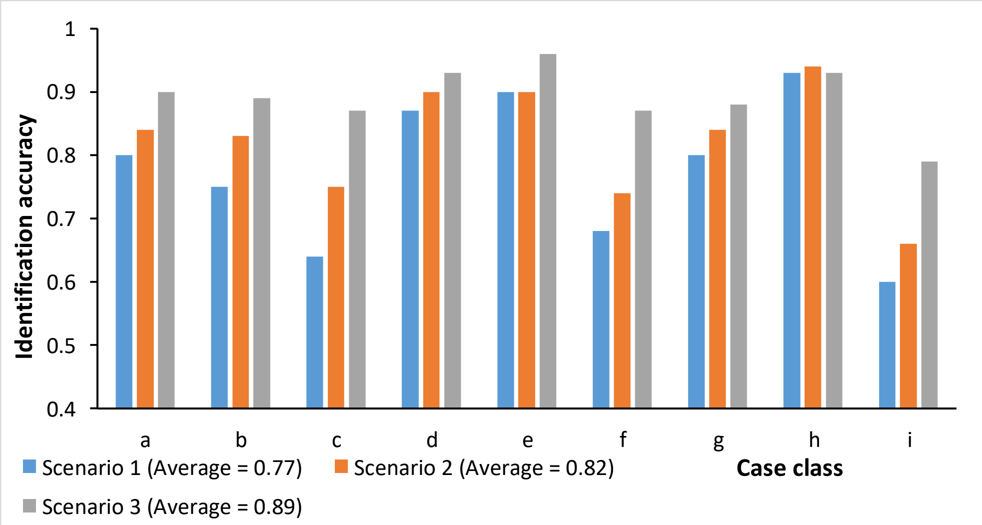

Fig. 10. The identification accuracy under different semantic ambiguity scenarios. The identification results in other metrics show similar trends (see Table 6). Scenario 1 is the original data imbalance scenario. In Scenario 2, transfer learning method is used without ontology modeling. In Scenario 3, ontology modeling is employed combined with transfer learning.

Table 6 Effect of semantic ambiguity on identification results. See Table 3 for the case class descriptions. Scenario 1 is the data imbalance scenario. In Scenario 2, transfer learning method is used without ontology modeling. In Scenario 3, ontology modeling is employed combined with transfer learning. Among the metrics, 'A' represents accuracy, 'P' represents precision, 'R' represents recall.

Scenario	Metric	a	b	c	d	e	f	g	h	i	Average
Scenario 1	A	0.80	0.75	0.64	0.87	0.90	0.68	0.80	0.93	0.60	0.77
	P	0.74	0.72	0.62	0.82	0.89	0.61	0.76	0.91	0.53	0.73
	R	0.72	0.70	0.61	0.81	0.88	0.59	0.73	0.90	0.50	0.72
	F1	0.73	0.71	0.61	0.82	0.89	0.60	0.75	0.91	0.51	0.73
	AUC	0.73	0.71	0.63	0.83	0.86	0.63	0.76	0.92	0.60	0.74
Scenario 2	A	0.84	0.83	0.75	0.90	0.90	0.74	0.84	0.94	0.66	0.82
	P	0.82	0.80	0.73	0.89	0.88	0.72	0.81	0.94	0.63	0.80
	R	0.82	0.80	0.73	0.88	0.88	0.72	0.81	0.94	0.62	0.80
	F1	0.82	0.80	0.73	0.88	0.88	0.72	0.81	0.94	0.62	0.80
	AUC	0.83	0.81	0.73	0.88	0.88	0.73	0.82	0.94	0.63	0.80
Scenario 3	A	0.90	0.89	0.87	0.93	0.96	0.87	0.88	0.93	0.79	0.89
	P	0.89	0.88	0.86	0.92	0.96	0.85	0.86	0.93	0.77	0.88
	R	0.89	0.87	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	F1	0.89	0.88	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	AUC	0.89	0.89	0.86	0.91	0.96	0.87	0.87	0.93	0.80	0.89

3.2 Comparison of proposed method with state of the art methods

The proposed method was also compared with existing methods to evaluate its performance on fire hazard identification under data imbalance. Four well-established machine learning and transfer learning methods have been compared in this paper, including SVM [17], FastText [39], TrAdaBoost (TrAdaB) [25] and Universal Language Model Fine-tuning (ULMFiT) [21]. Furthermore, three sampling-methods combined with SVM were also compared, including SVM with under-sampling [18], SVM with over-sampling [18] and SVM with Synthetic Minority Over-sampling Technique (SMOTE) [40]. In these ML experiments, identification performance was evaluated using five metrics, i.e. accuracy, precision, recall, F1 score and AUC. The abovementioned methods are illustrated as follows.

• **SVM**: Support Vector Machine is a traditional machine learning method without transfer learning. The SVM considers both experience risk and model structure risk, and thus has strong stability under uncertainties.

- **SVM with under-sampling**: Under-sampling method reduces data imbalance by randomly discarding some data of majority class. The effects of under-sampling can be observed when combined with traditional SVM.
- **SVM with over-sampling**: Over-sampling is another kind of sampling method which balances the data of different classes by repeatedly using some data of minority class.
- **SVM with SMOTE**: To avoid the overfitting problem in traditional over-sampling method, SMOTE was proposed to reduce data imbalance by generating synthetic samples instead of simply using existing samples.
- **FastText**: FastText is a famous deep learning method with a language model called n-gram. Compared to general ML methods, deep learning methods can describe complex feature relations using complex structures such as convolutional neural network (CNN).
- **TrAdaB**: TrAdaBoost is a typical transfer learning method using previous training data to help ML of newly added samples. The data distribution of the two domains is often different and thus this method can be applied to a number of scenarios as long as proper source domains are obtained.
- **ULMFiT**: Universal Language Model Fine-tuning is another famous transfer learning method where the discriminative fine-tuning and slanted triangular learning rates are used. This method transfers knowledge from the Internet and requires a pre-training model.

Table 7 shows the comparative results based on data from the Beidaihe area and the Lanzhou area. The proposed transfer learning method outperforms all the seven previously existing methods (with the overall accuracy, precision, recall, F1 score and AUC improved by 12%, 15%, 16%, 15% and 15%, respectively). In general, the transfer learning methods perform better than machine learning methods, which illustrates the important effect of knowledge transfer under data imbalance. Sampling-based methods significantly reduced data imbalance as the overall precision, recall and AUC were all improved. However, partly due to the lack of samples and features, the identification accuracy was not markedly improved when using sampling-based methods. Among the two transfer learning methods (TrAdaB and ULMFiT), ULMFiT performs better partly because of its big corpus. Compared to ULMFiT, the proposed method makes full use of cross-region knowledge and knowledge map, and gets a better performance.

4 Discussion

4.1 Applicability of the proposed method

The proposed transfer learning method for community fire hazard identification can be applied to a range of scenarios between (and excluding) two extremes: the extreme where all fire hazard related classes are strong classes in the community (Scenario 1) and the extreme where no fire hazard related class is strong class (Scenario 2). For Scenario 1, it often occurs when community management system has been introduced for years, with a number of fire hazard related cases accumulated (such as the scenario in Lanzhou Area). In this scenario, the transfer learning method is not needed as the pure learning approach could give enough good results. On the other hand, Scenario 2 often occurs at the early stage of using community management platform for fire hazard identification, with only small datasets can be obtained. The application of transfer learning in this scenario will cause huge communication cost as more than one time cross-region knowledge transfer may be needed to reach desired level of identification. The strength of the proposed method appears for scenarios in between where partial fire hazard related classes are strong classes. These scenarios are more realistic as most communities have established their own management information systems but the case data is imbalanced (such as Beidaihe Area). Hence, the proposed method achieves the cross-region complementarity of strong classes and improves the identification accuracy of local community with small communication cost. The proposed method achieves an identification performance that is clearly better than the performance for Scenario 2 and is higher than that of the pure learning approaches for Scenario 3 (where only partial strong classes exist).

Table 7 Identification results compared with existing methods. See Table 3 for the case class descriptions. Among the metrics, 'A' represents accuracy, 'P' represents precision and 'R' represents recall.

Method	Metric	a	b	c	d	e	f	g	h	i	Average
SVM	A	0.78	0.73	0.64	0.84	0.87	0.67	0.78	0.90	0.59	0.76
	P	0.74	0.71	0.60	0.81	0.84	0.59	0.74	0.89	0.53	0.72
	R	0.71	0.69	0.60	0.80	0.83	0.59	0.73	0.89	0.51	0.71
	F1	0.72	0.70	0.60	0.80	0.84	0.59	0.74	0.89	0.52	0.71
	AUC	0.71	0.70	0.61	0.82	0.84	0.61	0.75	0.89	0.60	0.72
SVM with under-sampling	A	0.75	0.71	0.61	0.83	0.85	0.66	0.76	0.90	0.58	0.74
	P	0.75	0.71	0.60	0.82	0.85	0.65	0.76	0.89	0.56	0.73
	R	0.74	0.70	0.59	0.81	0.84	0.64	0.75	0.89	0.56	0.73
	F1	0.74	0.70	0.59	0.81	0.85	0.64	0.75	0.89	0.56	0.73
	AUC	0.73	0.70	0.61	0.82	0.84	0.65	0.75	0.89	0.57	0.73
SVM with over-sampling	A	0.79	0.72	0.62	0.83	0.86	0.67	0.77	0.90	0.58	0.75
	P	0.80	0.73	0.62	0.83	0.85	0.67	0.77	0.90	0.59	0.75
	R	0.79	0.72	0.62	0.82	0.85	0.67	0.77	0.90	0.59	0.75
	F1	0.79	0.72	0.62	0.82	0.85	0.67	0.77	0.90	0.59	0.75
	AUC	0.79	0.72	0.62	0.83	0.86	0.66	0.77	0.90	0.59	0.75
SVM with SMOTE	A	0.80	0.75	0.65	0.84	0.87	0.71	0.80	0.92	0.62	0.77
	P	0.80	0.76	0.66	0.84	0.87	0.72	0.81	0.92	0.63	0.78
	R	0.80	0.75	0.66	0.84	0.87	0.71	0.80	0.91	0.62	0.77
	F1	0.80	0.76	0.66	0.84	0.87	0.72	0.81	0.91	0.62	0.78
	AUC	0.81	0.75	0.65	0.84	0.86	0.71	0.80	0.91	0.62	0.77
FastText	A	0.81	0.78	0.71	0.89	0.91	0.75	0.82	0.94	0.63	0.80
	P	0.78	0.76	0.68	0.86	0.90	0.72	0.81	0.93	0.61	0.79
	R	0.80	0.76	0.68	0.86	0.90	0.72	0.81	0.93	0.60	0.78
	F1	0.79	0.76	0.68	0.86	0.90	0.72	0.81	0.93	0.61	0.78
	AUC	0.79	0.76	0.69	0.85	0.91	0.73	0.80	0.93	0.61	0.79
TrAdaB	A	0.86	0.85	0.81	0.90	0.94	0.79	0.85	0.94	0.70	0.85
	P	0.84	0.83	0.78	0.89	0.94	0.78	0.83	0.94	0.68	0.83
	R	0.84	0.83	0.78	0.88	0.94	0.77	0.83	0.93	0.68	0.83
	F1	0.84	0.83	0.78	0.88	0.94	0.77	0.83	0.93	0.68	0.83
	AUC	0.85	0.83	0.79	0.88	0.93	0.78	0.83	0.93	0.68	0.84
ULMFiT	A	0.86	0.88	0.87	0.89	0.94	0.87	0.85	0.93	0.75	0.87
	P	0.85	0.86	0.86	0.87	0.94	0.85	0.83	0.92	0.73	0.86
	R	0.85	0.86	0.86	0.87	0.93	0.85	0.83	0.92	0.73	0.86
	F1	0.85	0.86	0.86	0.87	0.94	0.85	0.83	0.92	0.73	0.86
	AUC	0.86	0.87	0.85	0.88	0.93	0.86	0.84	0.92	0.73	0.86
Our Method	A	0.90	0.89	0.87	0.93	0.96	0.87	0.88	0.93	0.79	0.89
	P	0.89	0.88	0.86	0.92	0.96	0.85	0.86	0.93	0.77	0.88
	R	0.89	0.87	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	F1	0.89	0.88	0.85	0.92	0.96	0.85	0.85	0.93	0.77	0.88
	AUC	0.89	0.89	0.86	0.91	0.96	0.87	0.87	0.93	0.80	0.89

4.2 Strengths and weaknesses of the proposed approach

The proposed method has some strengths and weaknesses that need to be considered when comparisons are made with other approaches. On the one hand, the proposed method offers several strengths. First, the method gives a reasonable solution for citizen communication based fire hazard identification when case data imbalance exists, that is, partial fire hazard related cases classes are only with small datasets. Existing transfer learning methods for dealing with case data imbalance require both long text and openness of case content, e.g., by transferring public text from Internet datasets such as Wiki [41-43]. Secondly, the proposed method makes better use of available data through regional cooperation. In many communities, intelligent management systems are introduced for a short time with few daily service cases are accumulated. With the cross-region transfer learning, reasonable identification performance can be achieved without long-time data accumulation [14]. Thirdly, considering the incompleteness of key features for fire hazard identification, a knowledge map is embedded in the proposed method to supplement missing features, which distinguishes the proposed method from general transfer learning methods and makes it more practical in fire hazard identification. Fourthly, considering the semantic ambiguity of regions when applying cross-region knowledge transfer, the proposed method standardizes the cross-region features semantically by ontology modeling, and thus improves identification results. Fifthly, compared with typical TCA, the difference of samples' contribution to the domain distribution information is considered with a local discriminant analysis, which not only reduces the edge distribution difference and condition distribution difference between domains, but also improves the class separability of TCA.

Compared with traditional fire hazard identification methods, the proposed method identifies fire hazards by mining dynamic features in community daily service cases instead of analyzing fixed data items within plants or residential buildings, which shows the following advantages [16] [44]. First, the proposed method can be applied to identify various community fire hazards, especially outdoor fire hazards within communities. As mentioned at the beginning of this paper, the effects of traditional methods on community fire hazard identification are limited because those methods are basically designed for identifying fixed fire hazards within buildings instead of the various hazards around the communities. Secondly, the proposed method can lead to intelligent community fire hazard identification with reduced cost and high flexibility. Some existing methods identify residential fire hazards by analyzing sensor data (e.g. smoke detection) [45]. However, it is also unrealistic to install so many fire sensors at each part of communities (which is quite costly). Besides, the proposed method is designed for identifying fire hazards before a fire occurs, and thus there is plenty of time for hazard reduction.

On the other hand, one weakness of the proposed method is that its identification effect is constrained, that is, the identification accuracy of LC space (Target Domain) is generally lower than or close to that of the NC space (Source Domain) [46]. Consequently, the non-local communities which provide complementary strong classes are preferred in cross-region transfer learning. However, if government departments adopt powerful policy orientation to promote knowledge transfer cross regions, such constraints will be broken. Another weakness is that complete real-time identification is hard to realize with the proposed method as there will be a short time window till a fire hazard related case being reported by community workers or residents. This time window is very short and can be further shorten with the support of video monitoring and real-time social media platforms.

5 Conclusions and future work

This study addressed the problem of identifying community fire hazards from daily service cases under data imbalance situation. Particularly, considering the effects of text feature missing and cross-region semantic ambiguity on identification results, the cross-region transfer of identification knowledge was explored based on an improved transfer component analysis. The results (based on service cases of 9 fire hazard classes) show that under the data imbalance situation where there were only one strong classes, the overall identification performance was improved with overall accuracy, precision, recall, F1 score and AUC increased by 12%, 15%, 16%, 15% and 15%, respectively, which illustrates that the proposed approach can help realize accurate fire hazard identification even though data imbalance severely exists. Moreover, the proposed method can achieve desired performance with only half of the training samples (about two times of the samples in target domain). For the detailed classes, the identification performance of all the classes were improved with the number of weak classes reduced by 86% and the identification accuracy of class #c was improved from 64% to 87%. The proposed method was compared with existing machine learning and transfer learning methods. The experimental results show that the highest identification accuracy of state of art methods was 87% which was outperformed by the proposed method in which accuracy was 89%. In addition, the knowledge map and ontology modeling are proved helpful for improving cross-region knowledge transfer, which improved the overall identification accuracy by 2% and 7% respectively.

Several implications of the proposed transfer learning approach for fire hazard identification can be foreseen. Firstly, using the proposed method, various community fire hazards can be identified from citizen communication with small costs because basically no extra resources (e.g. workers and devices) are needed (except some basic communication devices). At the same time, compared with traditional ways (which absolutely rely on human work) of fire hazard identification, high efficiency and performance and can be achieved with intelligent methods (i.e. ML and TL methods). Secondly, the case data imbalance situation that affects the performance of community fire hazard identification can be addressed, since the proposed method only requires partial strong classes (those have already achieved desired identification performance even without transfer learning), while the identification results of the remaining classes can be improved based on the knowledge transfer from non-local communities (which have strong classes). Thirdly, for countries and regions that have just started using intelligent community management systems, the shortage of daily service cases can be addressed through the cross-region communication with the regions which have accumulated enough cases, which helps quickly realize accurate and intelligent identification of community fire hazards and facilitate the following fire risk assessment and response. Finally, the proposed method is expected to lead to more efficient fire hazard identification even under uncontrolled conditions.

There are several future directions that are worthy of investigation. For example, future studies can attempt to establish other structured, semi-structured or unstructured data that can be used to enhance the effect of transfer learning. In addition, it would be better to find out how to facilitate community fire hazard identification when large scale knowledge transfer is hard to realize for reasons such as policy orientation or high communication costs. Moreover, it can be explored whether the situations for knowledge transfer are different among different countries and how to design more targeted solutions. More extensive work can also focus at corresponding fire risk assessment and response methods with the support of smart fire hazard identification systems. Finally, it would be important and interesting to analyze the interaction between cities and communities for collaborative fire hazard management.

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